# COMPSCI 240: Reasoning Under Uncertainty 

Andrew Lan and Nic Herndon<br>University of Massachusetts at Amherst

Spring 2019

Lecture 12: Multiple Random Variables

## Recall: Random Variable

- A random variable is a function that maps from the sample space to the real numbers,

$$
X: \Omega \rightarrow \mathbb{R}
$$



## Multiple Random Variables

- Consider two random variables, $X$ and $Y$ associated with the same experiment.
- For $x, y \in \mathbb{R}$, we can define events of the form

$$
\{X=x, Y=y\}=\{X=x\} \cap\{Y=y\}
$$

- The probabilities of these events give the joint PMF of $X$ and $Y$ :

$$
p_{X, Y}(x, y)=P(X=x, Y=y)=P(X=x \text { and } Y=y)=P(\{X=x\} \cap\{Y=y\})
$$

- Useful for describing multiple properties over the outcome space of a single experiment, e.g., pick a random student and let $X$ be their height and $Y$ be their weight.


## Tabular Representation of Joint PMFs

| $\mathrm{P}(\mathrm{X}, \mathrm{Y})$ |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $\mathrm{X} \backslash \mathrm{Y}$ | $Y=1$ | $Y=2$ | $Y=3$ | $Y=4$ |
| $X=1$ | 0.1 | 0.1 | 0 | 0.2 |
| $X=2$ | 0.05 | 0.05 | 0.1 | 0 |
| $X=3$ | 0 | 0.1 | 0.2 | 0.1 |

- e.g., $P(X=2, Y=3)=$ ?, $P(X=3, Y=1)=$ ?, $\ldots$
- Given the joint PMF, can we compute $P(X=x)$ and $P(Y=y)$ ?

$$
\begin{aligned}
& p_{X}(x)=P(X=x)=\sum_{y} P(X=x, Y=y) \\
& p_{Y}(y)=P(Y=y)=\sum_{x} P(X=x, Y=y)
\end{aligned}
$$

- If we start with the joint PMF of $X$ and $Y$, we say $p_{X}(x)$ is the marginal PMF of $X$ and $p_{Y}(y)$ is the marginal PMF of $Y$.


## Computing Marginals from the Joint Distribution

- Suppose $Y$ takes the values $y_{1}, y_{2}, \ldots, y_{N}$, then

$$
\left\{Y=y_{1}\right\},\left\{Y=y_{2}\right\}, \ldots,\left\{Y=y_{N}\right\}
$$

form partitions of $\Omega_{Y}$.

- Hence, $\{X=x\}$ can be partitioned into

$$
\{X=x\} \cap\left\{Y=y_{1}\right\},\{X=x\} \cap\left\{Y=y_{2}\right\}, \ldots,\{X=x\} \cap\left\{Y=y_{N}\right\}
$$

- Therefore,

$$
\begin{aligned}
P(X=x)= & P(\{X=x\}) \\
= & P\left(\{X=x\} \cap\left\{Y=y_{1}\right\}\right)+P\left(\{X=x\} \cap\left\{Y=y_{2}\right\}\right) \\
& \quad \cdots+P\left(\{X=x\} \cap\left\{Y=y_{N}\right\}\right) \\
= & \sum_{y} P(\{X=x\} \cap\{Y=y\})=\sum_{y} P(X=x, Y=y)
\end{aligned}
$$

## Marginal PMFs

| $\mathrm{P}(\mathrm{X}, \mathrm{Y})$ |  |  |  |  | X | $\mathrm{P}(\mathrm{X})$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| X\Y | 1 | 2 | 3 | 4 |  |  |
| 1 | 0.1 | 0.1 | 0 | 0.2 | 1 | 0.4 |
| 2 | 0.05 | 0.05 | 0.1 | 0 | 2 | 0.2 |
| 3 | 0 | 0.1 | 0.2 | 0.1 | 3 | 0.4 |

## Marginal PMFs

| $\mathrm{P}(\mathrm{X}, \mathrm{Y})$ |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $\mathrm{X} \backslash \mathrm{Y}$ | 1 | 2 | 3 | 4 |
| 1 | 0.1 | 0.1 | 0 | 0.2 |
| 2 | 0.05 | 0.05 | 0.1 | 0 |
| 3 | 0 | 0.1 | 0.2 | 0.1 |


| Y | 1 | 2 | 3 | 4 |
| :---: | :---: | :---: | :---: | :---: |
| $\mathrm{P}(\mathrm{Y})$ | 0.15 | 0.25 | 0.3 | 0.3 |

## Example 1

| $\mathrm{P}(\mathrm{X}, \mathrm{Y})$ |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $\mathrm{X} \backslash \mathrm{Y}$ | 1 | 2 | 3 | 4 |
| 1 | 0.1 | 0.1 | 0 | 0 |
| 2 | 0 | 0.05 | 0.1 | 0.05 |
| 3 | 0.1 | 0.2 | 0.2 | 0.1 |

What's the value of $P(X=2, Y=3)$ ?
A: 0
B: 0.1
C: 0.05
D: 0.2
E: 1
Answer is $B$.

## Example 2

| $\mathrm{P}(\mathrm{X}, \mathrm{Y})$ |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $\mathrm{X} \backslash \mathrm{Y}$ | 1 | 2 | 3 | 4 |
| 1 | 0.1 | 0.1 | 0 | 0 |
| 2 | 0 | 0.05 | 0.1 | 0.05 |
| 3 | 0.1 | 0.2 | 0.2 | 0.1 |

What's the value of $P(X=3)$ ?
A: 0.1
B: 0.4
C: 0.05
D: 0.6
E: 1
Answer is D.

## Conditional PMFs

- Conditional PMF of $X$ given $Y$ :

$$
P(X=i \mid Y=j)=P(\{X=i\} \mid\{Y=j\})
$$

- Compute $P(X \mid Y)$ using the definition of conditional probability:

$$
P(X=i \mid Y=j)=\frac{P(X=i, Y=j)}{P(Y=j)}
$$

since for any two events $A, B$ we have $P(A \mid B)=\frac{P(A \cap B)}{P(B)}$.

- The conditional probability $P(X=i \mid Y=j)$ is the joint probability $P(X=i, Y=j)$ normalized by the marginal $P(Y=j)$.
- An equivalent definition of independence is $X$ and $Y$ are independent if

$$
\text { for all } i, j, \quad P(X=i \mid Y=j)=P(X=i)
$$

## Conditional PMFs

| $\mathrm{P}(\mathrm{X}, \mathrm{Y})$ |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $\mathrm{X} \backslash \mathrm{Y}$ | 1 | 2 | 3 | 4 |
| 1 | 0.1 | 0.1 | 0 | 0.2 |
| 2 | 0.05 | 0.05 | 0.1 | 0 |
| 3 | 0 | 0.1 | 0.2 | 0.1 |
|  | 1 | 2 | 3 | 4 |
| $\mathrm{P}(\mathrm{Y})$ | 0.15 | 0.25 | 0.3 | 0.3 |


| $P(X \mid Y)$ |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $\mathrm{X} \backslash \mathrm{Y}$ | 1 | 2 | 3 | 4 |
| 1 | 0.66 | 0.4 | 0 | 0.66 |
| 2 | 0.33 | 0.2 | 0.33 | 0 |
| 3 | 0 | 0.4 | 0.66 | 0.33 |

## Functions of Two Random Variables

Given two random variables $X$ and $Y$ and a function $f: \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$,

$$
Z=f(X, Y)
$$

is a new random variable. For example, pick random students and let $X$ be their height and $Y$ be their weight. If we define $Z$ as the Body Mass Index (BMI) where

$$
\mathrm{BMI}=\text { weight }(\mathrm{lb}) /(\text { height }(\text { in }))^{2} \times 703 .
$$

That is,

$$
Z=f(X, Y)=Y / X^{2} \times 703
$$

Then, $Z$ is also a random variable.

## Functions of Two Random Variables

The PMF of $Z$ can be expressed as

$$
p_{Z}(z)=\sum_{\{(x, y) \mid f(x, y)=z\}} p_{X, Y}(x, y) .
$$

For example, let us define a new random variable $Z=X \times Y$ where the joint PMF of $X$ and $Y$ is

| $\mathrm{P}(\mathrm{X}, \mathrm{Y})$ |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $\mathrm{X} \backslash \mathrm{Y}$ | 1 | 2 | 3 | 4 |
| 1 | 0.1 | 0.1 | 0 | 0 |
| 2 | 0 | 0.05 | 0.1 | 0.05 |
| 3 | 0.1 | 0.2 | 0.2 | 0.1 |

Then, the PMF of $Z$ looks like

| $Z$ | 1 | 2 | 3 | 4 | 6 | 8 | 9 | 12 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $P(Z)$ | 0.1 | 0.1 | 0.1 | 0.05 | 0.3 | 0.05 | 0.2 | 0.1 |

## Expectation and Variance of Two Random Variables

- The expected value and variance of $Z$ can be respectively computed as

$$
\begin{gathered}
E(Z)=\sum_{z} z P(Z=z)=\sum_{x, y} f(x, y) P(X=x, Y=y) \\
\quad=\sum_{x} \sum_{y} f(x, y) P(X=x, Y=y) \\
=\sum_{y} \sum_{x} f(x, y) P(X=x, Y=y)
\end{gathered}
$$

and

$$
\operatorname{var}(Z)=E\left(Z^{2}\right)-(E(Z))^{2}
$$

- If $X$ and $Y$ are independent, for all $x, y$

$$
P(X=x, Y=y)=P(X=x) P(Y=y)
$$

## Linearity of Expectation

- Lemma: Given two random variables $X, Y$, and $Z=X+Y$ then

$$
E[Z]=E[X+Y]=E[X]+E[Y]
$$

- Proof: Generalized expected value rule.

$$
\begin{aligned}
E[Z] & =\sum_{a} \sum_{b}(a+b) \cdot P(X=a, Y=b) \\
& =\sum_{a} \sum_{b} a \cdot P(X=a, Y=b)+\sum_{a} \sum_{b} b \cdot P(X=a, Y=b) \\
& =\sum_{a} a \sum_{b} P(X=a, Y=b)+\sum_{b} b \sum_{a} P(X=a, Y=b) \\
& =\sum_{a} a P(X=a)+\sum_{b} b P(Y=b) \\
& =E(X)+E(Y)
\end{aligned}
$$

## Expectation of Products of Independent Variables

- Lemma: If $X$ and $Y$ are independent then $E[X Y]=E[X] E[Y]:$
- Proof:

$$
\begin{aligned}
E[X Y] & =\sum_{a} \sum_{b} a b \cdot P(X=a, Y=b) \\
& =\sum_{a} \sum_{b} a b \cdot P(X=a) P(Y=b) \\
& =\sum_{a} a \cdot P(X=a) \cdot \sum_{b} b \cdot P(Y=b) \\
& =E[X] E[Y]
\end{aligned}
$$

## Variance of Sums of Random Variables

- Lemma: If $X$ and $Y$ are independent then

$$
\operatorname{var}(X+Y)=\operatorname{var}(X)+\operatorname{var}(Y)
$$

- Proof:

$$
\begin{aligned}
\operatorname{var}(X+Y)= & E\left[(X+Y)^{2}\right]-E[X+Y]^{2} \\
= & E\left[X^{2}+2 X Y+Y^{2}\right]-(E[X]+E[Y])^{2} \\
= & E\left[X^{2}\right]+2 E[X] E[Y]+E\left[Y^{2}\right] \\
& -\left(E[X]^{2}+2 E[X] E[Y]+E[Y]^{2}\right) \\
= & E\left[X^{2}\right]-E[X]^{2}+E\left[Y^{2}\right]-E[Y]^{2} \\
= & \operatorname{var}(X)+\operatorname{var}(Y)
\end{aligned}
$$

